Image Restoration from Subsampled STEM Measurements using Deep Learning

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Background

Scanning Transmission Electron Microscopy (STEM) has been shown to be a powerful tool for observing the atomic structure of complex materials. However, the radiation damage induced by the electron beam limits imaging beam-sensitive materials with acceptable signal-to-noise ratio.
Subsampled STEM [1] has recently been investigated as an approach for reducing the radiation damage without compromising the level of signal per each measurement (or probe position). It is achieved by subsampling the grid of probe positions, which results in an incomplete set of measurements. A complete STEM image is then recovered from those subsampled measurements through an inpainting process.

A myriad of inpainting methods have been introduced based on, e.g., variational [2], Plug-and-Play (PnP), and deep learning frameworks [3]. In this work, we focus on PnP methods, which have been widely used for solving various imaging problems by using an off-the-shelf denoiser as an image prior.

Methods

We propose a deep learning-based inpainting method. Inspired by the work on Deep Denoiser Prior (DDP) for image restoration [4], we utilize a pre-trained deep neural network as an implicit image prior and then integrate that pre-trained network into an iterative inpainting algorithm. We discuss how the training of a DDP can be improved using synthetic and experimental STEM images corrupted by different sources, such as detector noise, scan distortion, sample movement, and aberrations. Therefore, we also introduce a new tool for the fast generation of synthetic STEM images. Additionally, inspired by recent work on invariant priors [5], we demonstrate that enforcing equivariance to certain transformations, such as rotations, reflections, and translations, during the denoising step, improves the quality of inpainting.

Results

The results of our inpainting method are shown in Figure 1. The images tested in Figure 1 were not used for the training of the denoiser neural network. Ground truth synthetic images of $SrTiO_3$ and Si were generated using our image generation tool. These images were then randomly subsampled with respect to 25% of probe positions. Despite slight imperfections around the boundary of the images, marked by a yellow arrow, the reconstructed images are of very high quality, with Signal-to-Reconstruction Error Ratios (SREs) greater than 43 dB.

Conclusion

This work presents an inpainting method for subsampled STEM data that leverages the power of both variational and deep learning methods. Given the flexibility of PnP methods, any neural network architecture can be used as a DDP. In the future, we plan to extend this work to inpainting subsampled data in different modes of electron microscopy, such as scanning electron microscopy and 4-dimensional STEM.

Graphic:

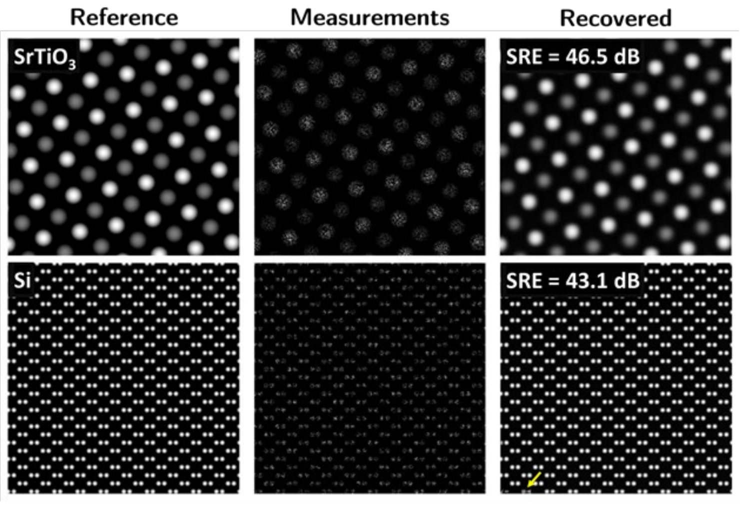

Figure 1. Examples of reference, measurements, and recovered images. Reference images are synthetically generated and were not used for training of the neural network. Measurements are generated by 25% subsampling of the probe positions at random. Signal-to-Reconstruction error Ratio (SRE) is shown in dB.

Keywords:

Deep Learning, STEM, Inpainting, Low-Dose

Reference:

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